

GIS-Based Analysis Framework to Identify the Determinants of COVID-19 Incidence and Fatality in Africa

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Abstract

Corona virus diseases 2019 (COVID-19) pandemic is an extraordinary threat with significant implications in all aspects of human life; therefore, it represents the most immediate challenge for the countries all over the world. This study, hence, is intended to identify the best GIS-based model that can explore, quantify, and model the determinants of COVID-19 incidence and fatality. For this purpose, geospatial models were developed to estimate COVID-19 incidence and fatality rates in Africa, up to 16th of August 2020 at the national level. The models involved Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) analysis using ArcGIS. Spatial autocorrelation analysis recorded a positive spatial autocorrelation in COVID-19 incidence (Moran index 0.16, $P = 0.1$) and fatality (Moran index 0.26, $P = 0.01$) rates within different African countries. GWR model had higher R^2 than OLS for prediction of incidence and mortality (58% vs 45% and 55% vs 53%). The main predictors of COVID-19 incidence rate were overcrowding, health expenditure, HIV infections, air pollution, and BCG vaccination (mean $\beta = 3.10, 1.66, 0.01, 3.79,$ and -66.60 respectively, $P < 0.05$). The main determinants of COVID-19 fatality were prevalence of bronchial asthma, tobacco use, poverty, aging, and cardiovascular diseases fatality (mean $\beta = 0.00162, 0.00004, -0.00025, -0.00144,$ and -0.00027 respectively, $P < 0.05$). Application of the suggested model can assist in guiding intervention strategies, particularly at the local and community level whenever the data on COVID-19 cases and predictors variables are available.

Keywords

COVID-19 incidence, Africa, GIS, COVID-19 case fatality, geographically weighted regression

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Introduction

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is a novel coronavirus that was first discovered at the end of 2019 in Wuhan, China after causing a cluster of pneumonic cases. In February 2020, the World Health Organization (WHO) designated the disease as coronavirus disease 2019 (COVID-19).¹ COVID-19 is the key global challenge nowadays with a lockdown of more than 6 billion people.² The rapid spread of SARS-CoV-2 resulted in an epidemic throughout China, followed by a massive spread across the globe. On March 11, 2020, WHO declared COVID-19 as a pandemic disease due to the increasing number of cases in a large number of countries all over the world at rapid rates and with high degrees of severity.³ Globally, up till the 13th of July 2021, more than 188 million individual caught the infection, with more than 4 million confirmed deaths. Africa reported approximately 6 million

COVID-19 cases and roughly 152 000 COVID-19 confirmed deaths.⁴

The transmission of COVID-19 is primarily through direct person-to-person transmission. Furthermore, it has been detected in non-respiratory specimens (stool, blood, ocular secretions, and semen), yet the role of these sites in the transmission is uncertain.⁵ Recently, airborne transmission was reported as a probable transport pathway to spread COVID-19.⁶ COVID-19 can be transmitted not only by symptomatic patients but also by asymptomatic

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individuals.⁷ Symptomatic patient infectiousness started 2.3 days before symptoms onset (peak 0.7 days before symptom onset) and declined within 7 days. After a week to 10 days there is no risk of disease transmission, primarily in individuals with mild infections who are immunocompetent. Overall, the level of closeness and duration of contact raises the risk of transmitting COVID-19 infection.⁸

For combating and proper management of COVID-19 spread, there is a need to understand the key determinants of its morbidity and mortality. Therefore, considerable number of research was undertaken to examine various determinants of COVID-19 incidence and fatality. Generally, weather conditions were suggested to have impacts on COVID-19 incidence. Wet and cold conditions were assumed to contribute to the rapid spread of COVID-19. In this respect, it was found that COVID-19 transmission and fatality were negatively correlated with temperature² and positively correlated with absolute humidity.^{6,9} Also, it was argued that air pollution can promote sustained transmission of COVID-19, where COVID-19 incidence was found to be positively correlated with atmospheric particulate matter and nitric oxide.¹⁰ The association between the particulate matter pollution and COVID-19 case fatality rate (CFR) was emphasized as well.¹¹ Moreover, the role of provision of adequate water, sanitation, and sanitary conditions during the pandemic of COVID-19 cannot be ignored as many studies have isolated the viral genome from stool samples.^{4,12} In the same context, Pung et al.,¹³ reported that the existing health security capacities are essential for tackling public health risks including infectious disease outbreaks such as COVID-19. In this respect, they found that half of the world countries lack sufficient operational readiness capacities for dealing with potential health emergencies associated with COVID-19.

As for socioeconomic and demographic, elderly are more susceptible to death after catching COVID-19.¹⁴⁻¹⁷ In addition, higher population density, poverty, urban residence were significantly associated with COVID-19 fatality.^{15,18} of note, both COVID-19 incidence and fatalities were found to be strongly associated with lower education levels,¹⁴ and tobacco smoking.¹⁵ Finally, the vulnerability of individuals to COVID-19 morbidity and mortality can be aggravated by having comorbid conditions like chronic diseases. Sanyaolu et al.,¹⁹ found that people who have comorbidities, such as hypertension or diabetes mellitus (DM), are expected to devel.

Regarding national control measures, many countries have adopted the national lockdown, limiting travel, and spatial rather than “social” distancing to control the local transmission of COVID-19.^{20,21} Such strategies were found to be effective to mitigate COVID-19 transmission.²²⁻²⁴ Limiting travel was found to have modest effect while transmission reduction measures like lockdown showed higher levels of effectiveness in the disease transmission control.²⁵ This generally implies that population mobility is one of the main determinants of COVID-19 incidence.

Mapping disease outbreaks can assist in understanding their key determinants. In this respect, thematic maps may be misleading in predicting the spatial pattern of the diseases. Alternatively, analyzing a spatial pattern is more effective as it implies assessing statistical significance of spatial clustering or dispersion, mapping clusters, if any, and modeling spatial relationships.²⁶ Accordingly, the key factors contributing to the diseases incidence and fatality can be determined.

In this research, authors aimed to model different environmental, socioeconomic, and demographic factors; health security capacity; comorbidities; and social mobility as predictors of the geospatial incidence and fatality of COVID-19 in 1 model. Such a geographic information system (GIS)-based model can provide better understanding of the key factors underlying COVID-19 incidence and fatality, which, in turn, may guide future intervention measures.

Methodology

To identify the key determinants of COVID-19 incidence (number of new cases/total population) and CFR (number of deaths due to COVID-19/number of COVID-19 affected patients), the research team identified the potential predictors of COVID-19 incidence and fatality. A preliminary list of COVID-19 incidence predictors was developed. The list of COVID-19 incidence contained 33 variables. Thereafter, these preliminary predictors were screened in accordance with some criteria such as relevance and data availability. Consequently, a short list of 14 variables of COVID-19 incidence was developed. The studied variables included demographic and socioeconomic conditions in addition to comorbidity, health security capacities, quality of life and population mobility. Meanwhile, a short list of 16 variables of COVID-19 fatality was developed. COVID-19 fatality predictors included demographic and socioeconomic conditions in addition to comorbidity and health security capacities (Table 1).

Collecting data on COVID-19 and potential predictors—Africa: up to the 16th of August 2020, data of the total confirmed cases and deaths at the national level—were retrieved from WHO portal. This website provides data on the global, regional, and country-level of COVID-19 newly reported cases and deaths on a regular basis.²⁷ Meanwhile, data of the predictor variables were acquired from The World Bank Group²⁸ and The Global Health Observatory.²⁹

Data Preparation

This involved developing a geodatabase for the African countries, including a key polygon feature class representing the territories of the African countries with their main attributes. Moreover, collected data on various predictors were tabulated and COVID-19 incidence and fatality rates were calculated. Thereafter, data on COVID-19 incidence as well

Table 1. List of potential predictors of COVID-19 incidence and fatality.

Potential predictors of COVID-19 incidence		
Categories	Predictors	Indicators
Socioeconomic and demographic predictors	Overcrowding	Population Density (person/km ²)
	Educational level	Illiteracy rate (%)
	Income	GDP per capita
	Poverty	Proportion of the population living in extreme poverty (%)
Comorbidity predictors	BCG vaccine	Proportion of 1-year old population immunized (%)
	HIV infections	Rate of HIV infections (per 1000 uninfected population)
	Tuberculosis incidence	Incidence of Tuberculosis (per 100 000 population)
Health security capacities predictors	Tobacco use	Prevalence of tobacco use among persons 15 years and older (%)
	Health expenditure	Domestic general government health expenditure (GGHE-D) as percentage of general government expenditure (GGE) (%)
Environmental factors	Stringency index	Government Response Stringency Index
	Using a hand-washing facility	Proportion of population using a hand-washing facility with soap and water (%)
	Access to drinking water services	Proportion of population using at least basic drinking water services (%)
	Access to sanitation services	Proportion of population using at least basic sanitation services (%)
Air pollution	Annual mean concentrations of fine particulate matter (PM2.5) in urban areas (µg/m ³)	
Potential predictors of COVID-19 fatality		
Categories	Predictors	Indicators
Socioeconomic and demographic predictors	Age Structure	Median age (year)
	Elder population	Proportion of elderly Population (Above 65 years old) (%)
	Human Development	Human development index
	Poverty	Proportion of the population living in extreme poverty (%)
Comorbidity predictors	Diabetes mellitus prevalence	Proportion of diabetic population (ages 20-79) (%)
	Cardiovascular fatality	Death rate from cardiovascular disease (per 100 000 people)
	Asthma prevalence	Proportion of asthmatic population (%)
	Cancer prevalence	Proportion of population Cancer (%)
	Human immune deficient virus (HIV) infections	New HIV infections (per 1000 uninfected population)
	Tuberculosis incidence	Tuberculosis incidence (per 100 000 population)
Health security capacities predictors	Tobacco use	Prevalence of tobacco use among persons 15 years and older (%)
	Density of physicians	Density of medical doctors (per 10 000 population)
	Density of nursery	Density of nursing and midwifery personnel (per 10 000 population)
	Density of pharmacist	Density of pharmacists (per 10 000 population)
	Health expenditure	Domestic general government health expenditure (GGHE-D) as percentage of general government expenditure (GGE) (%)
	Hospital beds ratio	Hospital beds per 1000 people

Abbreviations: BCG, Bacillus Calmette-Guérin; HIV, human immunodeficiency virus.

as potential predictors were integrated into the developed geodatabase through joined table tools in ArcGIS.

Spatial Analysis

This involves mapping COVID-19 incidence and evaluating the spatial pattern of COVID-19 incidence through Spatial Autocorrelation Tool (Moran's *I* index). To evaluate the distribution pattern of COVID-19 incidence and CFR,

spatial autocorrelation analysis (Moran's *I* index) was applied. Based upon its results, the spatial pattern of COVID-19 incidence and CFR was evaluated and outlier records, whether statistically or spatially, were excluded. Thereafter, the main hot spots were delineated through hot spot analysis. Meanwhile, the relationships between potential predictors as independent variables and COVID-19 incidence or fatality as dependent variable were calibrated, and the most significant independent variables were

identified through ordinary least squares tool (OLS). Finally, geographically weighted regression (GWR) was applied to explore the predictive power of such variables locally for each county, as it was not expected that COVID-19 driving factors would be uniform across different countries with varied conditions. GWR was initially introduced³⁰ to extend the traditional regression analysis for modeling local relationships between a certain phenomenon that is varied over space and several predictors so that the coefficients in the model rather than being constant are location-specified. Due to its analytical power, GWR was recently applied for modeling and explaining the spatial relationships in a variety of fields³¹⁻³³(see Supplemental Data 1).

As a prerequisite for GWR, there would be a need to evaluate multicollinearity among considered predictors (explanatory variables). For this purpose, a model was developed to estimate COVID-19 incidence and CFR in Africa up to the 16th of August 2020, at the national level, using variance inflation factor (VIF) analysis. The relationships between the explanatory variables and COVID-19 incidence and CFR rates were assumed to be the same at various countries. As a result of OLS model, the relationships between COVID-19 incidence and CFR on one hand and various considered explanatory variables, on the other hand, were found statistically insignificant. Also, it was found that some variables have large value of VIF, which indicate redundancy among these variables. Accordingly, through an iterative process, variables with large VIF value have been excluded stepwise and the remaining explanatory predictor variables in terms of COVID-19 incidence included: overcrowding, BCG vaccination, HIV infection, health expenditure, and air pollution. Meanwhile, the remaining explanatory predictor variables in terms of COVID-19 fatality were elder population, poverty, cardiovascular fatality, asthma prevalence, and tobacco use.

Results

Preliminary trials of spatial autocorrelation analysis revealed insignificant spatial autocorrelation in COVID-19 incidence and deaths rates due to the existence of outlier records, whether spatially such as Madagascar, or statistically such as South Africa, Gabon, and Djibouti. Therefore, these outliers were excluded. The results of Moran's *I* index revealed that there was positive spatial autocorrelation in COVID-19 incidence and CFR within different African countries. It was found that the Moran's *I* index for COVID-19 incidence rate recorded a small value (0.16), a relatively high *z*-score (1.67), and *P*-value (<0.10). Meanwhile, the Moran's *I* index for COVID-19 deaths rate recorded a relatively higher value (0.35), *z*-score (3.16), and smaller *P*-value (<0.01), which indicates that the relationship is more significant in the case of deaths compared to confirmed cases (see Supplemental Data 2).

Generally, it can be argued that, based on statistically significant *P*-value and high positive *z*-score, the spatial distribution of COVID-19 incidence and deaths rates tend to be clustered, and the null hypothesis of complete spatial randomness can be rejected. Hot spot analysis revealed that a cold spot of COVID-19 incidence and fatality rate in most African countries was noticeably identified in East of Africa (Figure 1a and b). Meanwhile, 3 hot spots of COVID-19 incidence rate were identified. These hot spots included Egypt and Libya in the northeast, Morocco, Mauritania, Senegal, and Gambia in the northwest, in addition to Namibia in the south (Figure 1a). Also, 2 hot spots of COVID-19 fatality were identified in the northeastern and northwestern parts of the continent (Figure 1b) corresponding to, but more significant compared to, the hot spots of incidence rate.

To identify the key predictors of COVID-19 incidence and fatality rates, GWR analysis through ArcGIS was applied. The results of OLS model showed that all explanatory variables of both COVID-19 incidence and fatality were statistically significant ($P < .05$). The results of OLS model showed that all explanatory variables of both COVID-19 incidence and fatality are statistically significant ($P < .05$). COVID-19 incidence rate was found to be positively associated with overcrowding ($\beta = 2.97$), health expenditure ($\beta = 1.45$), HIV infection ($\beta = .01$), and air pollution ($\beta = 3.29$) and negatively associated with BCG vaccine ($\beta = -47.65$). COVID-19 fatality was found to be positively related to asthma prevalence ($\beta = .00420$) and tobacco use ($\beta = .00005$) and negatively related to aging ($\beta = -.00258$), poverty ($\beta = -.00028$), and cardiovascular fatality ($\beta = -.00031$).

All the explanatory variables have noticeably small Variance Inflation Factor (VIF) values, which indicated non-redundancy among the considered explanatory variables. Generally, the results of OLS model are promising as the model recorded R^2 of 0.4535 in case of COVID-19 incidence and 0.5338 in case of fatality (Table 2). This means that the model explained about 45% and 53% of the variance in COVID-19 incidence and fatality rates, respectively.

The results of GWR were statistically more significant compared to OLS model, where the local produced R^2 in case of COVID-19 incidence ranged between 0.45 and 0.66 with an overall adjusted R^2 of 0.58. Meanwhile, local produced R^2 in case of COVID-19 fatality, was found to be more varied ranging between 0.34 and 0.85 with an overall adjusted R^2 of 0.55. This was highlighted by the standard variation, which is 2-fold that of incidence rate (Table 3). Generally, it should be noted that except for BCG vaccine, mostly the GWR model parameters were found to be less varied recording low standard deviation.

Also, it was noted that GWR model in case of COVID-19 incidence revealed higher explanatory power in western

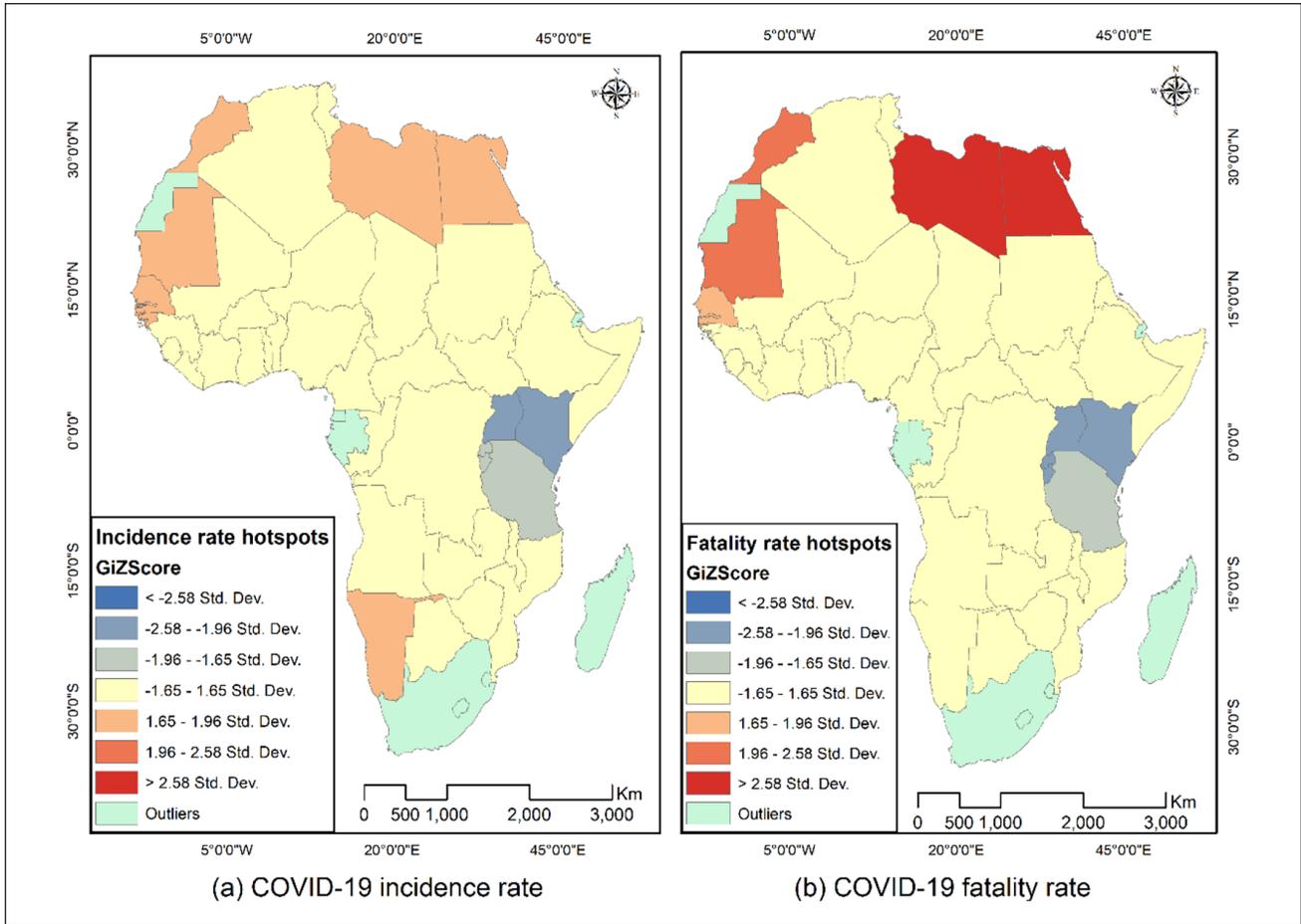


Figure 1. Hot spot analysis of COVID-19 incidence and fatality rates in Africa: (a) COVID-19 incidence rate and (b) COVID-19 fatality rate.

Table 2. Ordinary Least Squares Regression Model.

Variable	Coefficient (β)	t-Statistic	Probability	VIF
COVID-19 incidence				
Intercept	0.44514	1.97964	0.05543	—
Overcrowding	2.97288	4.31716	0.00012	1.08596
Health expenditure	1.45380	2.28912	0.02805	1.30737
BCG vaccine	-47.65202	-2.62772	0.01256	1.15719
HIV infections	0.01144	2.54531	0.01535	1.15583
Air pollution	3.28993	2.89638	0.00638	1.02464
R^2	0.45351			
COVID-19 fatality				
Intercept	0.01512	2.07490	0.04520	—
Elder population	-0.00258	-2.23400	0.03178	2.07770
Poverty	-0.00028	-3.77480	0.00058	1.97820
Cardiovascular fatality	-0.00031	-2.66490	0.01146	1.90340
Asthma prevalence	0.00420	3.10450	0.00370	2.72620
Tobacco use	0.00005	2.94160	0.00568	1.16880
R^2		0.53377		

Table 3. Coefficients, residual, and R^2 produced by (GWR) model.

Parameters	Minimum	Maximum	Mean	Standard deviation
COVID-19 incidence				
Intercept	0.28453	1.03252	0.58772	0.29922
Overcrowding (β)	1.98344	4.08228	3.10461	0.49437
Health expenditure (β)	0.19844	3.33230	1.66191	1.16584
BCG vaccine (β)	-128.33056	-20.09850	-66.60410	42.39930
HIV infections (β)	0.00539	0.01291	0.00986	0.00224
Air pollution (β)	3.06844	4.50561	3.78995	0.35991
Residual	-0.46329	0.47701	-0.00360	0.24063
Local R^2	0.44866	0.66377	0.56400	0.06736
Squared residuals	2.432547			
Overall Adjusted R^2	0.575972			
COVID-19 fatality				
Intercept	-0.00027	0.02214	0.01078	0.00644
Elder population (β)	-0.00354	0.00137	-0.00144	0.00117
Poverty (β)	-0.00038	-0.00016	-0.00025	0.00008
Cardiovascular fatality (β)	-0.00043	-0.00017	-0.00027	0.00007
Asthma prevalence (β)	0.00162	0.00625	0.15386	0.00366
Tobacco use (β)	0.00004	0.00006	0.00005	0.00001
Residual	-0.01115	0.01649	0.00010	0.00589
Local R^2	0.33673	0.85291	0.56072	0.14392
Squared residuals			0.00146	
Overall Adjusted R^2			0.54622	

and southern parts of Africa, compared to other parts of the continent (Figure 2a). In contrast, a higher explanatory power of GWR model in case of COVID-19 fatality was noted in the northeastern part of Africa and decreased noticeably westward and southward (Figure 2b). This means that the relationships between COVID-19 incidence and overcrowding, BCG vaccine, HIV infection, health expenditure, and air pollution can be more accurately captured in West Africa and sub-Saharan countries. Meanwhile, the relationships between COVID-19 fatality and elder population, poverty, cardiovascular fatality, asthma prevalence, and tobacco use can be more accurately captured in the north-eastern African countries.

The validity of GWR model results was emphasized by the low value of the squared residuals, which was found to be 2.432547 and 0.00146 in the case of COVID-19 incidence and fatality in Africa, respectively. Such a noticeably small value of squared residuals indicates slight difference between observed variable and its estimated value by GWR model and the model validity. Generally, GWR model revealed varied levels of accuracy in different African countries. This was highlighted by mapping residual values (Figure 3).

Moreover, GWR model predictions were evaluated through plotting COVID-19 incidence and fatality rate in different African countries, predicted by the suggested GWR model versus observed rates (Figure 4). In this

respect, the suggested GWR model revealed reasonable level of accuracy.

Discussion

Up till 16th of August 2020, African countries recorded 1.1 million confirmed cases of COVID-19 and more than 25 000 deaths. COVID-19 cases varied widely among different countries ranging between 583 653 cases in South Africa and 285 in Eretria. As for COVID-19 incidence rate, it was found to be about 0.97 (per 10^5 population) on average ranging between 0.009 and 9.97 (0.96 ± 1.69). Similarly, COVID-19 deaths per 10^5 population ranged between 0 in Eretria and 11 677 in south Africa (0.02 ± 0.03). Such noticeable high variations indicates uneven distribution of COVID-19 cases among different countries and can be attributed to the accuracy of registration procedures in these countries.

The results of regression model showed that COVID-19 incidence rate was found to be positively associated with overcrowding, HIV infection, health expenditure, and air pollution and negatively associated with BCG vaccine. The only exception was in the case of health expenditure that is supposed to be negatively related to COVID-19 incidence rate. This can be explained by the fact that high health expenditures usually implies improved health care capacities with better monitoring and registrations systems as

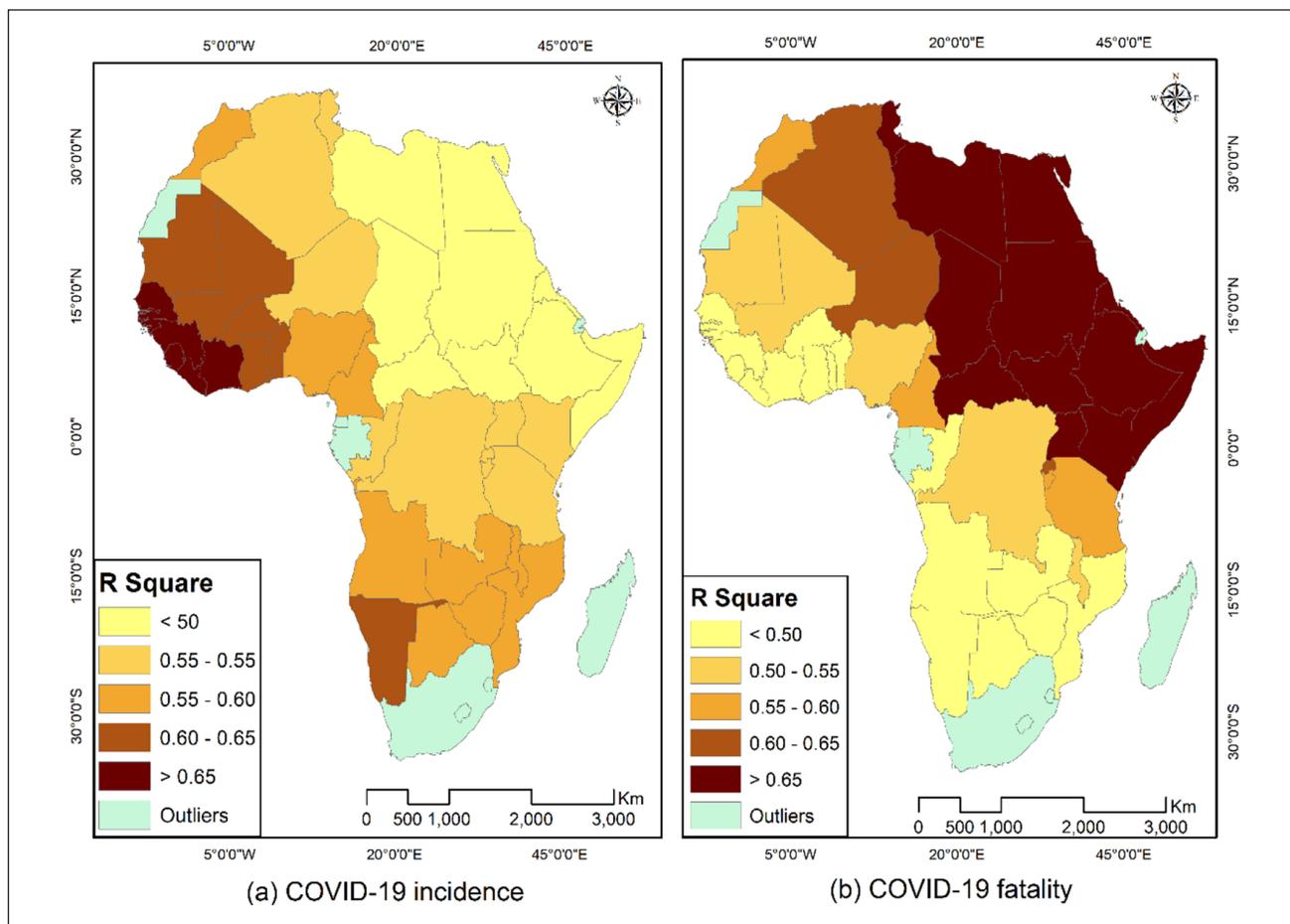


Figure 2. Spatial distribution of local R^2 of COVID-19 incidence and fatality rates: (a) COVID-19 incidence rate and (b) COVID-19 fatality rate.

well as COVID-19 testing. This, consequently, means more recorded cases compared to countries with lower health expenditure.

COVID-19 fatality was found to be positively related to asthma prevalence and tobacco use. Yet, certain level of inconsistency was noted in the case of COVID-19 fatality, which was negatively related to elder population, poverty, and cardiovascular fatality. The negative relationship between cardiovascular and COVID-19 fatality can be explained by inaccurate data on cardiovascular fatality due to inefficient national mortality registration systems in most African countries.³⁴ Meanwhile, the positive relationship between poverty and COVID-19 fatality can be justified by the fact that poverty usually implies lack of health insurance and less chance of getting hospitalized in case of infection, and less likely to be registered as a COVID-19 death incident.

Generally, the results of OLS model are promising as the model recorded R^2 of 0.4535 in case of COVID-19 incidence and 0.5338 in case of fatality. This means that

the model explained about 45% and 53% of the variance in COVID-19 incidence and fatality rates, respectively. However, such a relatively low level of explanatory power of the model can be justified by data accuracy and the nature of OLS itself that does not consider the local variations in COVID-19 incidence, fatality, and predictor variables. Accordingly, to increase the explanatory power of the model, GWR was applied considering spatial relationships between COVID-19 incidence as well as CFR and various predictors variables. The proposed GIS-based model showed high level effectiveness in exploring and modeling the relationships between COVID-19 incidence and CFR, on one hand, as dependent variables, and a number of relevant predictors as independent variables rate, on the other hand. Modeling such relationships requires using (OLS) and (GWR) in an integrated manner. The relationships between the COVID-19 incidence as well as fatality rates in Africa and various predictor variables have been quantitatively demonstrated through the proposed model.

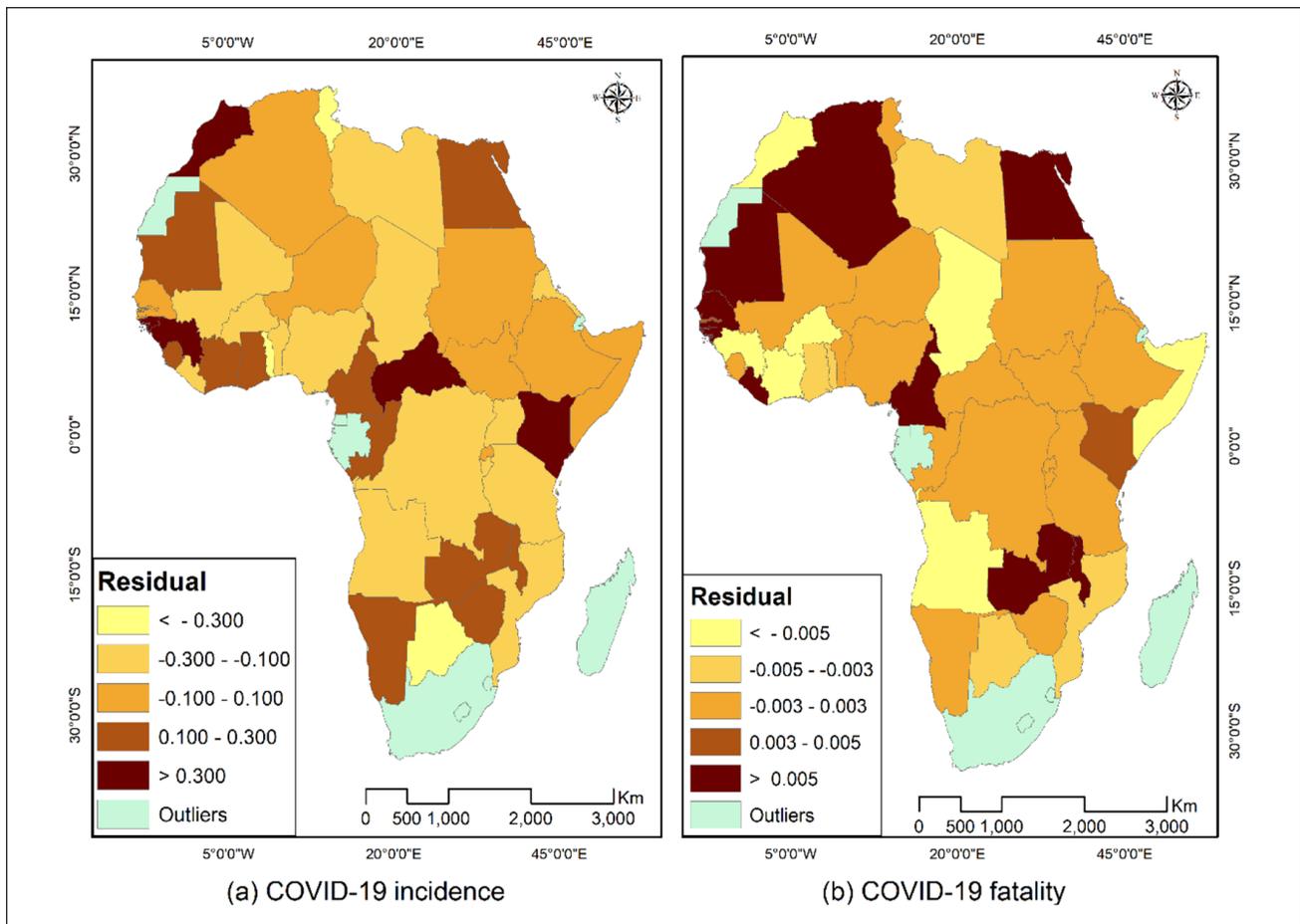


Figure 3. Spatial distribution of residual: (a) COVID-19 incidence rate and (b) COVID-19 fatality rate.

BCG Vaccine

Protective effect of BCG vaccine against COVID-19 is a debatable issue. In the current work, BCG vaccine was the most effective determinant of COVID-19 infection. Fu et al,³⁵ reported that at early stages of the pandemic, the BCG vaccination appears to have a significant protective effect, however, there is no compelling evidence that protection is provided at the latter phases. They also observe that in the early stages of a pandemic, a greater number of vaccinated young people may provide some amount of community protection against the virus, even if the proportion of vaccinated elderly people is low.

Overcrowding

We noticed that overcrowding was a strong predictor of COVID-19 incidence. In the same way, Rader et al³⁶ reported that population aggregation and heterogeneity greatly impact the degree to which COVID-19 cases are compressed into a short period of time (peak of the

epidemic), such that epidemics in crowded cities are more spread out through time, and crowded cities have higher overall attack rates than less populous ones.

Air Pollution

The current study demonstrated that air pollution was significantly associated with increased risk of COVID-19 infection. Through its impact on chronic diseases such as cardiopulmonary diseases and diabetes, air pollution may be linked to an increase in COVID-19 incidence and fatality. Air pollution causes a lowered immune response, which allows viruses to penetrate and replicate more easily. Viruses can survive in the air by interacting with particles and gases in complex ways that are influenced by chemical composition; particle electric charges; and meteorological conditions such as relative humidity, ultraviolet (UV) radiation, and temperature. Lastly, air pollutants may also promote viral persistence in the air and reduce vitamin D synthesis by reducing UV radiation.³⁷

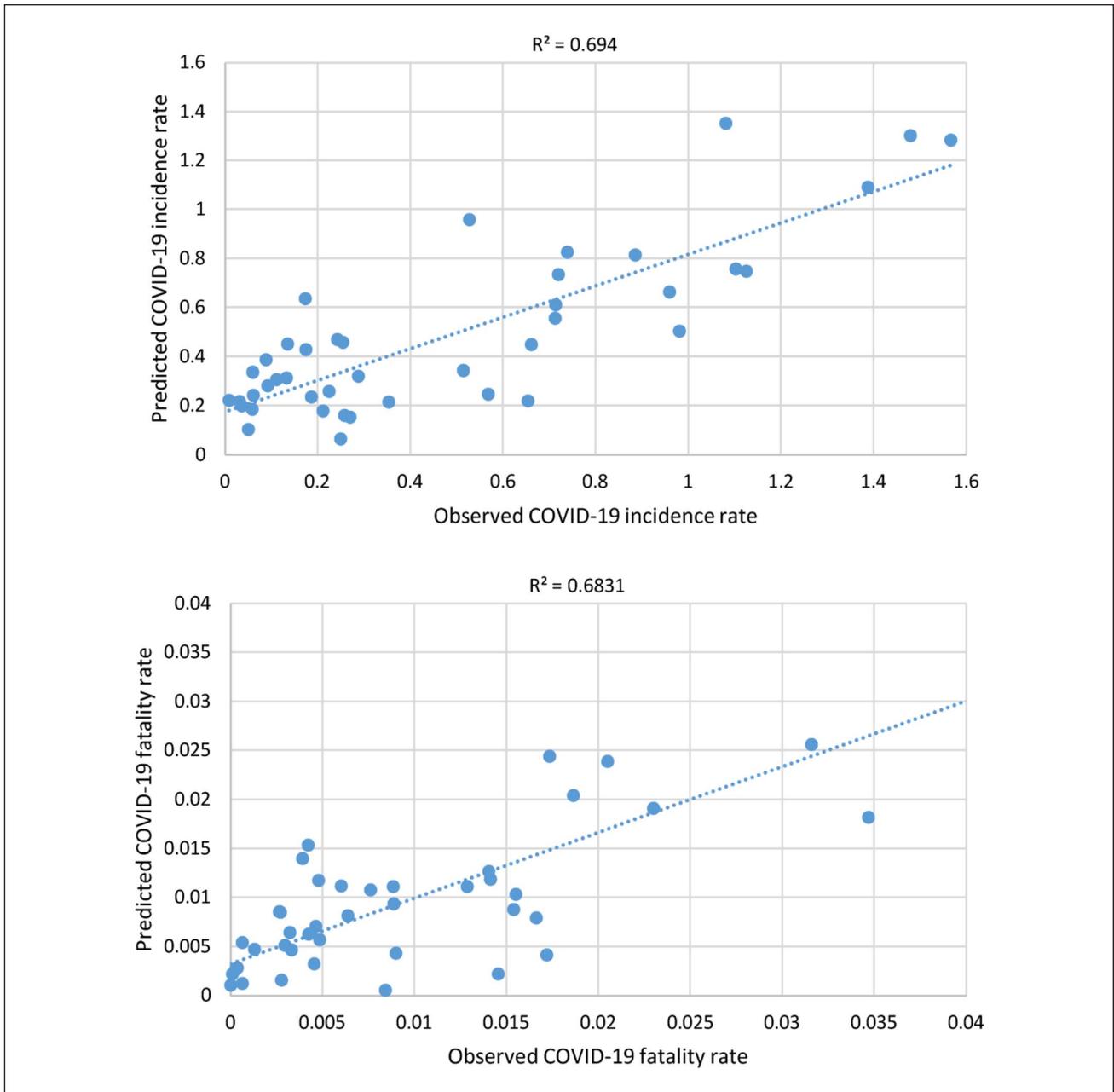


Figure 4. Observed versus predicted COVID-19 incidence and fatality rates in Africa.

HIV

Higher prevalence of HIV infection was associated with higher risk of COVID-19 transmission, nonetheless HIV infection was not significantly associated with increased CFR. On the other hand, in a large population-based study utilizing data from the OpenSAFELY platform in England, Bhaskaran et al,³⁸ discovered that black persons with HIV are prone to more than double the risk of COVID-19 mortality compared to persons without HIV, after accounting for demographic variables and lifestyle-related variables.

Smoking

In the current work, tobacco smoking significantly increased the risk of fatality among COVID-19 infected patients. Agreeing with our results, Umnuaypornlert et al³⁹ found that both current and former smokers had a higher risk of COVID-19 disease severity (OR=1.58; 95% CI: 1.16-2.15 and OR=2.48; 95% CI: 1.64-3.77 respectively). Furthermore, both current and former smoking substantially increase the risk of death among COVID-19 patients aged 65 years (OR=1.35; 95% CI: 1.12-1.62 and OR=2.58;

95% CI: 2.15-3.09, respectively). The angiotensin II conversion enzyme-2 (ACE2) receptor is abundant in mucosal epithelial cells and lung alveolar tissue and has been linked to COVID-19 infections. This is the most plausible explanation for the potential increase in risk. The host virus infecting the ACE2 receptors is most likely a crucial stage in coronavirus infection. After controlling for age, gender, and ethnicity, ACE2 gene expression is higher in current and past smokers compared to never smokers in a sample of lung adenocarcinoma patients.⁴⁰

Age

We found that aging was not a significant determinant of COVID-19 fatality. On the other hand, Yanez et al,⁴¹ declared that of 178 568 COVID-19 deaths among 2.4 billion individuals, people aged 65 years and over had significantly greater COVID-19 mortality rates than younger people, and males had a greater COVID-19 mortality risk. It well established that patients with comorbidities like hypertension, diabetes, bronchial asthma are more susceptible to COVID-19 related complication.^{9,19} Since the number of the comorbid illnesses increases with age, another possible reason for the observed higher mortality in older patients might exist.⁴² We speculate that reporting the cause of death as COVID-19 may be underestimated in African countries. As mentioned above elderly had multiple comorbidities that may make them more vulnerable to COVID-19 complications and death. Health authorities in developing countries may register another direct cause of death other than COVID-19 due to political issues, limited capacity of health service, or lower perceived risk of infection this may explain the insignificant effect of aging on COVID-19 related mortality.⁴³

Strength and Limitations

This is the first study that addresses the geospatial pattern of incidence and mortality across different African countries. The depended outcomes were not absolute numbers but the proportions of cases to total population or number of deaths to active cases. Another point of strength was that we already included more than 30 predictors subcategorized into environmental, sociodemographic, comorbidities, and health security capacity. Missing or incomplete data is the major limitation in this research. Indeed, during statistical analysis we adopted different strategies to deal with incomplete data like deletion, imputation, and regression. Finally, the accuracy of reporting of COVID-19 incidence and mortality was the main obstacle, however, we relied mainly upon data issued by WHO, which is most reliable source of data on COVID-19 cases and fatality worldwide.

Conclusion

The proposed geospatial model in this study suggested that overcrowding, BCG vaccine, HIV infection, health expenditure and air pollution are the key determinants of COVID-19 incidence in Africa. Similarly, old age, poverty, comorbidities like cardiovascular disease, bronchial asthma, and tobacco use were identified to be the key determinants of COVID-19 fatality rate in Africa. Furthermore, the proposed model can be downscaled to be applied to local and/or community levels. In such a case, the successful application of the GIS-based model suggested in this study depends largely on availability of updated, accurate, and detailed data on COVID-19 incidence and fatality as well as various considered predictors.

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Author Contributions

MH: designed the analysis framework and participated in writing the manuscript. TE and RA: were responsible for collecting data, data validation and performing the analysis. RMG: Conceptualization of the research idea, shared in data collection, and writing the manuscript.

Declaration of Conflicting Interests

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Supplemental Material

Supplemental material for this article is available online.

References

1. WHO. Coronavirus disease (COVID-19) pandemic. WHO. [Updated 2020 August 9, cited 2021 May 9]. https://www.who.int/emergencies/diseases/novel-coronavirus-2019?gclid=Cj0KCCQjwvb75BRD1ARIsAP6LcquozuVw17Rf-LzW-sU1adVciTrGOydDS-8wTDOIO3hj3IJXL8WL7GwkaA-jlQEALw_wcB
2. Iqbal MM, Abid I, Hussain S, Shahzad N, Waqas MS, Iqbal MJ. The effects of regional climatic condition on the spread of COVID-19 at global scale. *Sci Total Environ*. 2020;739:140101. doi:10.1016/j.scitotenv.2020.140101

3. García-Basteiro AL, Chaccour C, Guinovart C, et al. Monitoring the COVID-19 epidemic in the context of wide-spread local transmission. *Lancet Respir Med.* 2020;8(5):440-442. doi:10.1016/s2213-2600(20)30162-4
4. WorldoMeter. Coronavirus updates. [Updated 2021 May, cited 2021, July 13]. <https://www.worldometers.info/coronavirus/>
5. American Association of Blood Banks. AABB's Coronavirus resources. [updated 2021 May, cited December 18 2020]. <http://www.aabb.org/advocacy/regulatorygovernment/Pages/AABB-Coronavirus-Resources.aspx>
6. Pani SK, Lin NH, RavindraBabu S. Association of COVID-19 pandemic with meteorological parameters over Singapore. *Sci Total Environ.* 2020;740:140112. doi:10.1016/j.scitotenv.2020.140112
7. Rothe C, Schunk M, Sothmann P, et al. Transmission of 2019-nCoV infection from an asymptomatic contact in Germany. *N Engl J Med.* 2020;382(10):970-971. doi:10.1056/NEJMc2001468
8. He X, Lau EHY, Wu P, et al. Temporal dynamics in viral shedding and transmissibility of COVID-19. *Nat Med.* 2020;26(5):672-675. doi:10.1038/s41591-020-0869-5
9. Asem N, Ramadan A, Hassany M, et al. Pattern and determinants of COVID-19 infection and mortality across countries: an ecological study. *Heliyon.* 2021;7(7):e07504-e07504. doi:10.1016/j.heliyon.2021.e07504
10. Li H, Xu XL, Dai DW, Huang ZY, Ma Z, Guan YJ. Air pollution and temperature are associated with increased COVID-19 incidence: a time series study. *Int J Infect Dis* 97:278-282. doi:10.1016/j.ijid.2020.05.076
11. Yao Y, Pan J, Wang W, et al. Association of particulate matter pollution and case fatality rate of COVID-19 in 49 Chinese cities. *Sci Total Environ.* 2020;741:140396. doi:10.1016/j.scitotenv.2020.140396
12. Zhang Y, Chen C, Zhu S, Shu C. Isolation of 2019-nCoV from a stool specimen of a laboratory-confirmed case of the coronavirus disease 2019 (COVID-19). *China CDC Weekly.* 2020:123-124.
13. Pung R, Chiew CJ, Young BE, et al. Investigation of three clusters of COVID-19 in Singapore: implications for surveillance and response measures. *Lancet.* 2020;395(10229):1039-1046. doi:10.1016/s0140-6736(20)30528-6
14. Hawkins RB, Charles EJ, Mehaffey JH. Socio-economic status and COVID-19-related cases and fatalities. *Public Health.* 2020;189:129-134. doi:10.1016/j.puhe.2020.09.016
15. Baron YM. Incidence and case-fatality ratio of COVID-19 infection in relation to tobacco smoking, population density and age demographics in the USA: could particulate matter derived from tobacco smoking act as a vector for COVID-19 transmission? *medRxiv.* 2020;doi:10.1101/2020.10.04.20206383
16. Goldstein JR, Lee RD. Demographic perspectives on the mortality of COVID-19 and other epidemics. *Proc Natl Acad Sci USA.* 2020;117(36):22035-22041. doi:10.1073/pnas.2006392117
17. Omori R, Matsuyama R, Nakata Y. The age distribution of mortality from novel coronavirus disease (COVID-19) suggests no large difference of susceptibility by age. *Sci Rep.* 2020;10(1):16642. doi:10.1038/s41598-020-73777-8
18. Finch WH, Hernández Finch ME. Poverty and Covid-19: rates of incidence and deaths in the united states during the first 10 weeks of the pandemic. *Front Sociol.* Published online June 15, 2020. doi:10.3389/fsoc.2020.00047
19. Sanyaolu A, Okorie C, Marinkovic A, et al. Comorbidity and its impact on patients with COVID-19. *SN Compr Clin Med.* 2020;2:1069-1076. doi:10.1007/s42399-020-00363-4
20. Bi Q, Wu Y, Mei S, et al. Epidemiology and transmission of COVID-19 in 391 cases and 1286 of their close contacts in Shenzhen, China: a retrospective cohort study. *Lancet Infect Dis.* 2020;20(8):911-919. doi:10.1016/s1473-3099(20)30287-5
21. Tian H, Liu Y, Li Y, et al. An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science.* 2020;368(6491):638-642. doi:10.1126/science.abb6105
22. Kraemer M, Yang C, Gutierrez B, et al. The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science.* 2020;368:493-497. doi:10.1126/science.abb4218
23. Zhao S, Zhuang Z, Cao P, et al. Quantifying the association between domestic travel and the exportation of novel coronavirus (2019-nCoV) cases from Wuhan, China in 2020: a correlational analysis. *J Travel Med.* 2020;27(2): taaa022. doi:10.1093/jtm/taaa022
24. Asem N, Ramadan A, Hassany M, et al. Pattern of COVID-19 infection and death across countries: a pilot study. *Heliyon.* 2021:e07504. doi:10.1016/j.heliyon.2021.e07504
25. Chinazzi M, Davis JT, Ajelli M, et al. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science.* 2020;368(6489):395. doi:10.1126/science.aba9757
26. Fischer MM, Getis A. *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications.* Springer; 2010.
27. WHO. *COVID-19 Weekly Epidemiological Update;* 2020:23.
28. The World Bank Group. Indicators. The World Bank Group. Accessed December 14, 2020. <https://data.worldbank.org/indicator/>
29. WHO. The global health observatory. WHO. Accessed November 10, 2020. <https://www.who.int/data/gho/data/indicators>
30. Brunson C, Fotheringham AS, Charlton ME. Geographically weighted regression: a method for exploring spatial nonstationarity. *Geog Anal.* 1996;28(4):281-298.
31. Cahill M, Mulligan G. Using geographically weighted regression to explore local crime patterns. *Social Sci Comput Rev.* 2007;25(2):174-193.
32. Huang Y, Leung Y. Analysing regional industrialisation in Jiangsu province using geographically weighted regression. *J Geog Syst.* 2002;4:233-249.
33. Mennis J. Mapping the results of geographically weighted regression. *Cartographic J.* 2013;43(2):171-179. doi:10.1179/000870406x114658
34. Rao C, Bradshaw D, Mathers CD. Improving death registration and statistics in developing countries: lessons from sub-Saharan Africa. *South Afr J Demogr.* 2004;5(2):81-99.
35. Fu W, Ho P-C, Liu C-L, et al. Reconcile the debate over protective effects of BCG vaccine against COVID-19. *Sci Rep.* 2021;11(1):1-9.

36. Rader B, Scarpino SV, Nande A, et al. Crowding and the shape of COVID-19 epidemics. *Nat Med*. 2020;26(12):1829-1834.
37. Bourdrel T, Annesi-Maesano I, Alahmad B, Maesano CN, Bind M-A. The impact of outdoor air pollution on COVID-19: a review of evidence from in vitro, animal, and human studies. *Eur Respir Rev*. 2021;30(159):200242.
38. Bhaskaran K, Rentsch CT, MacKenna B, et al. HIV infection and COVID-19 death: a population-based cohort analysis of UK primary care data and linked national death registrations within the OpenSAFELY platform. *Lancet HIV*. 2021;8(1):e24-e32.
39. Umnuaypornlert A, Kanchanasurakit S, Lucero-Prisno DEI, Saokaew S. Smoking and risk of negative outcomes among COVID-19 patients: a systematic review and meta-analysis. *Tob Induced Dis*. 2021;19.
40. Bauer CM, Morissette MC, Stämpfli MR. The influence of cigarette smoking on viral infections: translating bench science to impact COPD pathogenesis and acute exacerbations of COPD clinically. *Chest*. 2013;143(1):196-206.
41. Yanez ND, Weiss NS, Romand J-A, Treggiari MM. COVID-19 mortality risk for older men and women. *BMC Public Health*. 2020;20(1):1-7.
42. Kang S-J, Jung SI. Age-related morbidity and mortality among patients with COVID-19. *Infect Chemother*. 2020;52(2):154.
43. Chitungo I, Dzobo M, Hlongwa M, Dzinamarira T. COVID-19: unpacking the low number of cases in Africa. *Public Health Pract (Oxf)*. 2020;1:100038-100038. doi:10.1016/j.puhip.2020.100038